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Semantic Space: Bridging the divide between cognitive science, information processing technology and quantum mechanics

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Abstract

Human beings are adept at drawing context-sensitive associations and inferences across a broad range of situations ranging from the mundane to the creative inferences that lead to scientific discovery. Such reasoning has a strong pragmatic character and is transacted with comparatively scarce cognitive assets. The question is how to get technology to reliably replicate this? The need for such technology is pressing. Paradoxically, the information explosion is leading to diminished awareness. Expertise is becoming ever more specialized: Individuals, groups, communities, enterprises are becoming increasingly insular. We need computational systems which have the capability to enhance our awareness, for example, by suggesting associations in context that we could make, but increasingly don't, as we generally lack the cognitive resources to do so. The premiss behind this paper is that the technology has to manipulate context sensitive meanings which accord with those that we harbour. In other words, the "meanings" manipulated by the technology should be socio-cognitively motivated. A class of cognitively validated computational model called "semantic space" is introduced together with means for computing associations between words. It is argued that such associations can be usefully deployed to underpin human pragmatic reasoning. The paper concludes with some intriguing, highly speculative connections between semantic space and quantum mechanics.

1. Introduction

Peter and Rupert pass in the hallway of an Australian ICT research organization. Peter, a research scientist utters to Rupert, the business development manager, "How is it going with John?" This utterance is the tip of an iceberg rich in implicit associations: Due to their shared con-

text, Peter and Rupert both know that "John" refers to "John Smith" of "ACME Corp", who are negotiating a license for "Guidebeam", a particular web-based search technology.

In the not so distant future our information environment will feature all sorts of devices and displays. Imagine the existence of a context manager which processes the above utterance, draws appropriate context sensitive associations in order to flesh it out, and thereafter uses the result to query for emails, license documents, podcasts of relevant conversations etc., and tacitly retrieves these to prime Rupert and Peter's immediate information environment. For example, pointers to relevant documents could be brought up on the wall display should they be needed for further reference in Peter and Rupert's discussion.

Sometimes drawing an association between concepts can lead to scientific discovery. In the mid nineteen eighties, Don Swanson's made a chance discovery. One day, while browsing PubMed, an online repository of biomedical literature, he notices the properties of dietary fish oil would seem to address the symptoms of Raynaud's disease. Patients with Raynaud's disease suffer from intermittent blood flow in the extremities - fingers, toes, and ears. At the time, there was neither a general treatment, nor a cure. Swanson's serendipitous association firms into an explanatory hypothesis that fish oil is a treatment for Raynaud's disease. He discharged his hypothesis in an article, and a subsequent clinical trial confirms it. Being an information scientist, Swanson performed a citation analysis of researchers around Raynaud's disease and those around dietary fish oils. The respective research communities are disjoint [35, 37]. Swanson's discovery highlights a more widely occurring phenomenon. In order to deal with the information explosion, disciplines and expertise are becoming increasingly specialized and insular with little awareness of kindred, or potentially allied, specializations. As a consequence, disparate bodies of knowledge form, and with them "undiscovered public knowledge" [36].

The above two scenarios attempt to highlight the need for technology which can draw context-sensitive, and at times highly creative associations, which accord with those we would make. Such associations are often implicit as shown by Swanson's discovery. It would be a misunderstanding to construe this need as motivation for a rehash of a program in artificial intelligence (AI). Certainly, symbolic AI has made impressive progress in producing theoretical models of human practical inference by exploration into non-monotonic reasoning (NMR). There remains, however, a dearth of large-scale operational NMR systems plying their wares on the ground. This lack can be traced back to drawbacks of the symbolic approach, whereby knowledge is represented in propositional form and inference is transacted by means of logical deduction [18]. One crucial drawback highly relevant to this project is the slippery notion of context. In symbolic approaches, there have been attempts to model, represent, infer context, but the solutions have only been of a theoretical nature. The inability of symbolic systems to deal effectively with context is tied intimately to the "frame problem". In a thought provoking book, Gärdenfors argues that the frame problem can be circumvented by considering knowledge representation at the conceptual level of cognition, that is *below* the symbolic level of cognition. In addition, NMR systems are driven by deduction, which contrasts the scenarios above in which inference has a decidedly associational, and at times *abductive* character. Finally, the complexity issues of NMR systems have been well documented in the AI literature. These results make their deployment on a large scale problematic.

2. Dimensional representations "down below"

Swanson's discovery is an example of a mode of reasoning known as abduction. Gabbay and Woods [17] have convincingly argued that abduction has its roots in cognitive economy. Put crudely, it is cheaper to "guess", than to pursue a deductive agenda in relation to a problem at hand. It is interesting to briefly consider Gabbay and Woods' conjecture within the framework of Gärdenfors' three level model of cognition [18]. How information is represented varies greatly across the different levels. Within the lowest level, information is pre- or sub-conceptual and is carried by a connectionist representation. Within the uppermost level information is represented symbolically. It is the intermediate, conceptual level (or "conceptual space"), which is of particular relevance to this account. Here properties and concepts have dimensional representations. For example, the property of "redness" is represented as a convex region in a tri-dimensional space determined by the dimensions hue, chromaticity and brightness. The point left dangling for the moment is that representation at the conceptual level is rich in associations, both explicit and implicit. The

present author subscribes to the view that associations and analogies generated within conceptual space play an important role in hypothesis generation. Gärdenfors ([18], p48) alludes to this point when he states, "most of scientific theorizing takes place within the conceptual level". His conjecture is aligned with Gabbay and Woods' insights regarding the cognitive economic basis of abduction: Within the conceptual space, inference takes on a decidedly associational character because associations are often based on context-sensitive similarity (e.g., semantic or analogical similarity), and notions of similarity are naturally expressed within a dimensional space. Inference at the symbolic level, however, is transacted in a linear, deductive fashion. It may well be that because associations are formed below the symbolic level of cognition, significant cognitive economy results. This is not only interesting from a cognitive point of view, but also opens the door to providing both a principled and computationally tractable system that can produce sorts of context-sensitive associations we make, not only for scientific discovery, but in day-to-day garden variety situations like Peter and Rupert meeting in the hallway.

In light of the introductory remarks above, it is our conviction that it would be misguided to adopt a traditional, symbolic perspective by assuming a propositional knowledge representation and proof-theoretic approaches for driving it. Gabbay and Woods [15] argue that this perspective is conceptually incomplete - it ignores what is going on "down below". In terms of Gärdenfors' model, "down below" can be interpreted as the conceptual and sub-conceptual levels of cognition. Even if one does not accept Gabbay and Woods' objection, another can be mounted from an operational stance. Textual information like that used by Swanson cannot automatically be rendered into a propositional representation. In addition, deductive approaches have well documented and daunting complexity results. Granted, the complexity challenges can be to a degree circumvented by the use of heuristics, but the dearth of large-scale symbolic logical systems reasoning over text suggests significant operational challenges not likely to be surmounted soon. For these reasons, we feel strongly that from both the conceptual and operational perspectives, a purely symbolic approach does not pave the way towards abductive systems. It is our conviction that in order to construct such systems, a cognitively motivated knowledge representation is required. More specifically, we advocate semantic spaces as a computational approximation of Gärdenfors' conceptual space. We shall see hypotheses generated from semantic spaces do not have a proof-theoretic basis, but rather they are computations of associations by various means within the space.

	ben	eff	of	fish	oil	on	bld	visc
ben								
eff	5							
of	4	5						
fish	3	4	5					
oil	2	3	4	5				
on	1	2	3	4	5			
bld		1	2	3	4	5		
visc			1	2	3	4	5	

Table 1. Example HAL matrix.

3. Approximating Cognitive Knowledge Representation by Semantic Space

In order to illustrate how the gap between cognitive knowledge representation and actual computational representations can be bridged, the Hyperspace Analogue to Language (HAL) model is presented [27]. HAL produces representations of words in a high dimensional space that seem to correlate well with equivalent human representations. Burgess, Livesay and Lund [11] note “...simulations using HAL accounted for a variety of semantic and associative word priming effects that can be found in the literature...and shed light on the nature of the word relations found in human word-association norm data”.

HAL takes a corpus of text as input and learns a representation of words by accumulating weighted associations of co-occurring words in the context of fixed length window. More specifically, given a vocabulary of n words drawn from the corpus in question, HAL computes an $n \times n$ matrix by moving a window of length l over the corpus by one word increments, ignoring punctuation, sentence and paragraph boundaries. All words within the window are considered as co-occurring with strength 1. When the counts of the sliding window are aggregated, the strength of association between words becomes proportional to the distance between the words, because words that are closer together co-occur in more windows. Each row i in the matrix represents the accumulated weights of association of words that occur before i within context windows. Conversely, column i represents the accumulated weights of association of words that appear after i within context windows. By way of illustration, table 1 depicts a HAL matrix constructed from the text “Beneficial effect of fish oil on blood viscosity”, with $n = 8$ and $l = 5$.

If word order information is not considered important, the HAL matrix can be added to its transpose resulting in a symmetric matrix. In the context of table 1, the term “fish” would be represented by (ben: 3, eff: 4, of: 5, fish: 0, oil: 5, bld: 4, visc: 3). The row and column vectors are added together, thus combining pre and post co-occurrence counts.

<i>Dimension</i>	<i>Value</i>
nifedipine	0.44
scleroderma	0.36
ketanserin	0.22
synthetase	0.22
sclerosis	0.22
thromboxane	0.22
prostagalndin	0.22
dazoxobin	0.21
E1	0.15
calcium	0.15
vasolidation	0.15
platelet	0.15
...	...
platelets	0.07
blood	0.07
viscosity	0.07
vascular	0.07
...	...

Table 2. Example HAL representation of the concept “Raynaud”.

The column vectors of the symmetric HAL matrix are then normalized to unit length.

In practice, different variations of semantic space are possible. For example, stop words such as “the”, “on”, “of”, etc. may be ignored. Also, HAL is but one scheme for computing term co-occurrence weights. Other weighting schemes include log-likelihood [13] and odds-ratio [26].

Table 2 shows part of the normalized HAL vector for the word “Raynaud” computed by applying the HAL method to a collection of 111,603 titles of core journal documents drawn from the MEDLINE collection (the dimensions are ordered by decreasing strength of association). This example demonstrates how a word is represented as a weighted vector whose components correspond to other words. The weights represent the strengths of association between “Raynaud” and other words with which it co-occurred within the context of the sliding window. The Raynaud vector is therefore an aggregated representation of the contexts in which the word “Raynaud” appears within the collection.

The quality of HAL vectors is influenced by the window size: the longer the window, the higher the chance of representing spurious associations between terms. A window size of eight or ten has been used in various studies [27, 11, 8].

More formally, a semantic space S used in this article is an $n \times n$ matrix, where n is the size of the term vocabulary. $S[i, j]$ denotes the strength of context-sensitive co-occurrence of the terms i and j . The vector representation

of a word j is the j th column of S , and is denoted: s_j . The length of the vector s_j is given by:

$$|s_j| = \sqrt{\sum_{i=1}^n S[i, j]^2}$$

A vector s_j is normalized to unit length by dividing each of its components by the length of the vector:

$$\text{normalize}(s_j) = \frac{s_j}{|s_j|}$$

The field of cognitive science has recently produced an ensemble of semantic models which have an encouraging, and at times impressive track record of replicating human information processing, such as human word associations norms [27, 11, 25, 26, 22, 23, 33, 24, 34, 19]. The term “semantic” derives from the intuition that words seen in the context of a given word contribute to its meaning. Colloquially expressed, the meaning of a word is derived from the “company it keeps”¹ [14]. Although the details of the individual models differ, they all process a corpus of text as input and represent words, or concepts, in a (reduced) high dimensional space. These models are interesting in light of the problem just presented as they open the door to gaining operational command of cognitive semantics and associated human pragmatic inference mechanisms. Even though there is ongoing debate about specific details of the respective models, they all feature a remarkable level of compatibility with a variety of human information processing tasks such as word association. Semantic spaces provide a geometric, rather than propositional, representation of knowledge. They can be considered to be approximations, albeit primitive, of the conceptual space proposed by Gärdenfors [18].

From an operational perspective, semantic spaces have been constructed from very large collections of text, for example, a corpus of Usenet news comprising 160 million words [27], so they have a demonstrated track record of knowledge representation in the large.

In short, semantic spaces are a promising, pragmatic means for large-scale socio-cognitively motivated knowledge representation. Moreover, due to their cognitive credentials, semantic spaces would seem to be apt foundation for underpinning computational variants of human practical reasoning, like abduction.

4. Abduction in Semantic Space

Human abductive reasoning has been modeled in terms of a filtration structure [16, 17]. This can be imagined

as funnel taking a space of possibilities and refining them through successive filters. More specifically, *Gen* is a sublogic which generates a set of suggestions U . Next, the engagement sublogic, *Engage*, engages those elements of U relevant to the problem at hand. The result of *Engage* is a proper subset R of U , the set of relevant suggestions for possible consideration. In turn, the plausibility filter contracts R to a set of possibilities for actual consideration, represented by P . Finally, the discharge sublogic *Dis* transforms the plausible suggestions into a premise (or premises). The distinction between a suggestion and premise is important. Agent X may consider several suggestions in relation to agenda A that X wishes to close, but a premise is a suggestion which X is willing to discharge. In summary, the triple (U, R, P) represents a filtration structure on the initial set of suggestions, in which succeeding sets are cut downs of their predecessors.

Suggestions can be computed from semantic space as follows. A corpus of text is identified and a semantic space is constructed from it, for example, by using HAL. Typically agent X will not be totally ignorant, but rather will be aware of certain aspects of the agenda which can be used as initial trigger points of exploration into the problem space. These aspects are dubbed triggers. An initial trigger t is a word or concept providing an entry point into the problem space surrounding agent X 's agenda A . The task is to produce relevant and plausible associations from the underlying semantic space. By way of illustration, consider agenda A to be opening up a coffee shop in an urban region whose affairs fall under the jurisdiction of more than one layer of government, and where the services of relevance cut public and private boundaries. Pertinent services span beyond the various tasks of business registration into a spectrum of issues such as occupational health and safety, tax, employment, future natural resources plans, market demographic viability, incubation subsidies and personal investment leverage etc. This example, reminiscent of planning activities, demonstrates a need for services not easily satisfied by perusing ranked lists of service descriptions. Abduction from semantic space, on the other hand, can help the user navigate a complex problem space by providing suggestions for services which they may not be able to formulate themselves as (s)he lacks the epistemic resources to do so. For example, when the service for obtaining a food licence has been completed, the system could suggest a service for a music licence, or one for footpath dining, say (The human agent may easily neglect or be ignorant that such issues need to be considered). In other words, the goal of the suggestions is to discover additional triggers of which the agent may not be aware. In other words, triggers can lead to the discovery of other triggers. In this way, the agent can begin to construct a map of the problem space. In short, the suggestions will hopefully provide clues for retrieving

¹Semantic space models normally do not take word order into account - a recent advance is the BEAGLE model [19, 20]

and coming to know the information necessary to close the (sub)agenda at hand.

In the following, the letters i, j, k represent arbitrary words in the semantic space and s_i, s_j and s_k represent the associated vector representations. The integer n refers to the dimensionality of semantic space S .

In the literature, the cosine between s_i and s_j gives a measure of the semantic association between terms i and j . (See, for example [23]). The assumption underlying cosine is the smaller the angle between i and j , the higher the strength of semantic association:

$$\cos(s_i, s_j) = \text{normalize}(s_i) \cdot \text{normalize}(s_j) \quad (1)$$

where \cdot denotes the scalar, or “dot product of the respective unit vectors.

The Minkowski family of metrics includes the Euclidean distance metric ($r = 2$) which, like cosine, has also been employed with encouraging success in replicating human semantic association norms with HAL [28, 11]:

$$\text{mink}(s_i, s_j) = \sqrt[r]{\sum_{k=1}^n |S[k, i] - S[k, j]|^r} \quad (2)$$

Vector negation in semantic space can be used to refine the relevance of suggestions computed from semantic space. It allows agent X to bring to bear what X already knows, or needs to know, in relation to a (sub)agenda. This is achieved by expressing aspect X wishes to exclude in relation to a concept at hand. For example, in relation to the coffee shop, X may be interested to close a sub-agenda dealing with employee issues, but agent X is not interested in the aspect of compensation. This is expressed as the vector negation “employee NOT compensation. Vector negation in semantic space has been used to good effect in stripping out word senses [41, 38]:

$$i \text{ NOT } j \equiv s_i - \frac{s_i \cdot s_j}{|s_j|^2} s_j \quad (3)$$

where j is a term representing the aspect to be ignored, and is the norm of vector s_j . Vector negation has been generalized to $i \text{ NOT } (j_1 \text{ OR } \dots \text{ OR } j_k)$ allowing k irrelevant aspects of i to be excluded. Even though the disjunction $(j_1 \text{ OR } \dots \text{ OR } j_k)$ is a subspace of the semantic space, the expression can be computed as single scalar product thereby facilitating its efficient computation [38]. In it worth mentioning in passing that vector negation is motivated from quantum logic which raises the intriguing question as to what is quantum about semantic space? More about this shortly.

The above equations are now placed in the context of the filtration structure (U, R, P) of human abductive reasoning presented earlier. Cosine, Minkowski, vector negation can

all be used to operationalize the sublogic *Gen* which computes suggestions u which populate U in relation to a given trigger t . Cosine and Minkowski allow suggestions to be ordered on decreasing strength of association to t . For example, if cosine is used, the suggestions will be ordered on decreasing cosine (increasing angle) with t . In order to prevent information overload, only highly ranked associations could be shown to agent X .

The sublogic *Engage* endeavours to deliver relevant suggestions from the space U . Research into data mining has repeatedly shown that its relatively easy to compute associations; computing relevant associations is much harder. In fact, the dearth of suitable operational models of relevance hampers many computational disciplines. Essentially the ranking of suggestions is a pragmatic means to fulfill *Engages* function with the assumption that highly ranked associations are more likely to be relevant.

Finally, agent X s peruses the ranking produced by sublogic *Gen* and identifies those suggestions u which are plausible for closing a (sub)agenda, for example, by searching for appropriate services related to u . The *Dis* sublogic is ultimately the province of agent X , as (s)he will ultimately chose those suggestions deemed worthy of discharge.

Abductive systems computing associations from semantic space in the above fashion have been deployed in literature-based discovery [9, 3, 5], social network discovery in online communities [29, 30, 31].

5. The Quantum Mechanics of Semantic Space

Recently a highly speculative but potentially far reaching discovery was made by a group of physicists: The formalization of quantum mechanics (QM) shows very strong connections with the mathematical basis of semantic space models [2]. What are the implications of this intriguing connection?

In order to provide some intuition about how QM relates to semantic space, consider the word “suit”. In isolation it is ambiguous - it may refer refer to an item of clothing, a legal procedure, or even a deck of cards. However, when seen in the context of the word “grey”, the ambiguity resolves into the sense of the word dealing with clothing. The connection with QM is the following. The “meanings” of words in semantic space are superposed in a way which is intuitively similar to a quantum particle represented by the state vector $|\psi\rangle$. When the state $|\psi\rangle$ is measured it “collapses”, thus, after the measurement it is no longer in a superposition state, but rather it is in *one* of the possible states exemplified by the eigenstates of the operator depicting the measurement. In other words, measurement of a property to a high degree of accuracy erases all information about other properties of the state. “Measurement” of word senses appears to be the same; a sufficiently strong context erases all infor-

mation about the other senses. An appropriate analogy is the Necker cube², which is an ambiguous line drawing. The human perceptual mechanism will switch between alternate interpretations of the drawing, but both interpretations *cannot* be perceived simultaneously.³ Recent work has shown how the collapse of word meanings onto a sense parallels quantum collapse [4, 1, 41, 10]. Admittedly this work is highly speculative and QM is basically only being used as a metaphor. However, it is important to stress how the issue of context has been modelled as a “measurement” - seeing a word in the contexts of other words acts like a measurement. QM is perhaps the only theory in which the issue of context is neatly embedded into the theory itself and therefore offers the promise for gaining better command of contextual issues [21], and thus hopefully better relevance judgments in relation to computing associations from semantic space.

Given the purported similarities between the formal basis of QM and semantic space models, perhaps the most intriguing and speculative question is whether there is something akin to quantum entanglement in semantic space. Consider twin state photons prepared in one of the so called Bell states. Measurement of the polarization of one of the twins collapses its state onto polarization “up” say, but also instantaneously collapses the state of the other twin even if they are separated by galactic distances. The analogy with semantic space is the following. In general the words *Reagan* and *North* would be distant in human semantic space, however, according to the intuition above, seeing *Reagan* in the context of *Iran* leads the collapse of *Reagan* onto a basis state (sense) of President Reagan dealing with the Iran-Contra scandal which in turn may influence the collapse of *North* onto the Iran-Contra basis state, i.e., *Oliver North* who was a central figure in the scandal. One could say the words “Reagan” and “North” act like the twin state photons in human semantic space - their meanings are entangled given the context word “Iran”. Experiments have been proposed for testing for the entanglement of words in human semantic space [6]. This work is based on the conjecture of Nelson & McEvoy, two prominent human memory researchers that words in memory may be “associatively entangled” [32].

One way to illustrate where further investigations may potentially lead is to reconsider the Raynaud/fish oil connection in the light of quantum theory [39]. The illustration derives from the following speculation: Can the concepts “Raynaud” and “fish oil” be viewed as being entangled in semantic space? This seemingly wild speculation has two important aspects. The first is cognitive, namely, that entanglement in semantic space parallels entanglement in conceptual space (that is in human cognition). The second is

the potential bearing on (semi-)automated knowledge discovery systems. It has been shown that the statistical connection between the concepts “Raynaud” and “fish oil” is statistically weak [3]. As a consequence, it is challenging to build automated knowledge discovery systems using models based on classical probability theory. Assuming that the quantum entanglement of concepts does manifest in semantic space models, and furthermore, the entangled concepts represent potentially meaningful connections, then this may lead to radically different information retrieval and knowledge discovery technology than currently exists. Such research can be more broadly placed within the endeavours of the emerging field of “quantum interaction” the goal of which is to apply quantum theory outside of physics [40, 7].

Finally, we return again to Peter and Rupert’s hallway conversation. In the not so distant future our information environment will feature all sorts of devices and displays. Imagine the existence of a context manager which processes their utterances, draws appropriate context sensitive associations in order to flesh it out, and thereafter uses the result to tacitly query for emails, license documents, podcasts of relevant conversations etc. to prime Rupert and Peter’s immediate information environment. Such technology must be able to process meanings as well as symbols. Moreover, these meanings are context sensitive and socio-cognitively situated. The inferences being drawn are associational and rely on semantic processing. Quantum theory is a new frontier for drawing theoretical inspiration for the development of what could become a new genre of information processing technology.

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²http://en.wikipedia.org/wiki/Necker_cube

³Interestingly, Conte et al. [12] have proposed a quantum-like model for such Gestalt phenomena.

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